Power Grid Optimal Topology Control Considering Correlations of System Uncertainties

Mohannad Alhazmi, *Student Member, IEEE,* Payman Dehghanian, *Member, IEEE,*
Shiyuan Wang, *Student Member, IEEE*, and Bhavesh Shinde, *Student Member, IEEE*

***Abstract*—This paper presents a probabilistic formulation and solution technique for the application of DC optimal power flow (DCOPF)-based network topology control through the transmission line switching strategies. Efficient utilization of the point estimation method (PEM) is pursued to model the system uncertainties, i.e., the stochastic load profile and the intermittent renewable generation. In order to address the computational effectiveness of the suggested probabilistic methodology, the PEM formulation is harnessed by a scenario reduction approach to capture the correlations of the system uncertainties, thereby achieving a more robust and faster operation solution for day-ahead and real-time applications. The proposed approach is applied to a modified IEEE 118-bus test system, where it demonstrates its attractive performance under different test scenarios.**

***Index Terms*—Correlation; network topology control; probabilistic; switching; uncertainty.**

NOMENCLATURE

A. Sets

$n \in \Omega_B$	Set of system buses.
$g \in \Omega_G$	Set of system generating units.
$k \in \Omega_L$	Set of system transmission lines.
$z \in \Omega_Z$	Set of uncertain variables.

B. Variables and Functions

$f_X(.)$	Probability density function of variable X.
$\overline{GC^t}$	Expected total system generation dispatch cost probabilistically realized at time t.
G_W	Output power of a wind turbine (in MW).
P_{D_n}	Vector of demand (in MW) at load bus n.
$\overline{P^t_{d_n}}$	Expected active power of bus n at time t.
$\overline{P^t_{gn}}$	Expected power output of generator g at bus n at time t.
$P^{Wind}_{g,n}$	Wind generation output at bus n.
P^t_{knm}	Power flow through transmission line k (connecting bus n to m) at time t.
$P_{z,i}, \lambda_{z,i}$	Probability and Skewness of concentration i for random variable k.
υ	Wind speed (m/s).
X, Y	Vectors of random input and output variables.
α_k	Switch action for transmission line k (1: no switch, 0: switch).
θ_n	Voltage angle at bus n.
$x(.), (.)$	Concentrations of X.
σ_x, μ_x	Standard deviation and mean value of random variable x.
$J(.)$	Joint distribution function of random variables.

C. Dual Variables

η	Lagrange multipliers for equality constraints.
π	Lagrange multipliers for inequality constraints.

D. Parameters

B_k	Susceptance of transmission link k.
c_{g_n}	Linear generation cost of generating units g at bus n.
$E(.)$	Expected value.
$K, K^{'}, K^{''}$	Parameters of wind turbines.
M_k	Big-M value corresponding to transmission line k.
$P^{min}_{gn}, P^{max}_{gn}$	Minimum and maximum generation limit of generator g at bus n.
P^{min}_k, P^{max}_k	Minimum and maximum limit on the power flow of transmission line k.
P_r	Rated power of a wind turbine (in MW).
$\upsilon_i, \upsilon_r, \upsilon_o$	Cut-in, rated, and cut-out wind speed (m/s).
r	Number of PEM input random variables.
$w(.), (.)$	Weighting factor.
$\xi(.), (.)$	Location of concentrations.
$\theta^{min}_n, \theta^{max}_n$	Minimum and maximum voltage angle at bus n.
ψ, β	Shaping and scaling coefficients of the Weibull probability distribution.

I. INTRODUCTION

POWER system topology control or transmission line switching (TLS) has been recognized, in theory and practice, as a viable solution in hour- and day-ahead operations of electric transmission power grids [1], [2]. Utilizing the network existing infrastructure during the grid normal operating conditions, TLS results in a notable operational cost reduction. TLS can be also approached as a corrective action for power grid reliability improvement during critical contingencies [3], mitigation of voltage violations [4] and line overloads [5], ensuring system security [6], congestion management [7], and load outage recovery [8], [9]. Continuous variations in the electricity demand and the inherent uncertainties in renewable

978-1-5386-7551-9/19/$31.00 ©2019 IEEE

energy resources, if not modeled and handled properly, may compromise the application and attractiveness of the TLS technology in real-world practices.

In the past few decades, an eminent number of contributions have been recorded on hypothetical foundations with deterministic models and formulations for TLS applications in modern power transmission systems, primarily to achieve higher economic benefits and financial gains [10]–[14]. AC formulation of the topology control optimization is introduced in [15]. The effect of deterministic TLS on various electricity market features, with and without taking into account the N-1 reliability criterion, were investigated in [16], [17]. Heuristic optimization models to handle the computational complexities of the large-scale TLS optimization problem are proposed in [18]–[20]. In dealing with the system uncertainties in TLS formulations, [21] studies a deterministic approximation with chance-constrained formulation for topology control deployment in power systems primarily to accommodate higher utilization of wind generation. Robust optimization, where only the worst case uncertainty scenario is taken into account resulting in the most conservative TLS solutions, is suggested in [22]. For applications to large-scale power grids in presence of a significant number of system uncertainties (stochastic load and intermittent renewables), a manageable-size and tractable formulation based on robust optimization models may not be computationally feasible.

To the best of the authors' knowledge, there has been limited effort on modeling and incorporating the correlation of system uncertainties into the TLS optimization formulations. This paper puts forward a unique perspective to the conventional deterministic TLS optimization formulations. This paper (i) introduces a probabilistic topology control formulation that can capture major uncertainties in the grid and stochastically assimilate such probabilistic features in network topology control optimization and (ii) implements a scenario reduction technique driven by the correlation of system uncertainties to make this stochastic optimization model computationally friendly and tractable.

The rest of the paper is organized as follows. Section II presents background information on the topology control formulations for economic benefits. Section III introduces the proposed probabilistic optimization problem and the solution technique with the corresponding mathematical formulations. Section IV presents the numerical case studies and simulation results, followed by the paper conclusions in Section V.

II. Power System Topology Control

A. Deterministic TLS Models and Formulations

Deterministic transmission line switching (DTLS) formulations assume that renewable generations and loads are all known at a given time instant with accurate forecasts available [23]. The system uncertainties are neither modeled nor incorporated. Typical formulations are based on DC Optimal Power Flow (DCOPF) in hour-ahead or day-ahead applications and results in system minimum-cost solutions with transmission lines switching statuses. DTLS optimization can be also modeled in an AC setting where the solutions are more accurate, while the computational burden is more extensive.

B. Probabilistic TLS Models and Formulations

Probabilistic analysis is becoming increasingly important since (i) deterministic analysis cannot fully disclose the state of the system and (ii) many random distortions or uncertainties arisen from the measurement errors, forecasting errors, etc. exist. Uncertainties driven by renewable portfolios and the load variability are modeled in the probabilistic transmission line switching (PTLS) formulations. Such probabilistic DCOPF-based optimization models are developed to find the optimal hour-ahead solution for network topology and generation dispatch that result in significant economic savings. In such formulations, uncertainties should be first modeled and characterized, then embedded into the PTLS optimization models.

1) Uncertainty Characterization of Renewables and Loads: Probability density function (PDF) and historical data are employed in this paper to model the uncertainties driven by the high penetration of wind generation and the variable behavior of loads in the system. However, other approaches such as time series, artificial neural network, and regression techniques can be used to serve the same goal [24], [25]. The hourly wind speed is modeled by a Weibull probability distribution with the PDF expressed in (1) [26]. The model captures the sequential characteristic of the wind velocity and its impact on the output power of wind turbines. It has been proven that (1) gives a fairly applicable and accurate characterization of the wind speed [26], [27]. The PDF parameters are statistically estimated using the historical wind speed data by applying the curve fitting methods and maximum likelihood estimations. The output power of the wind generator is probabilistically calculated as a function of wind speed, formulated in (2).

$$f_v(v) = \left(\frac{\psi}{\beta}\right)\left(\frac{v}{\beta}\right)^{\psi-1} e^{-\left(\frac{v}{\beta}\right)^{\psi}} \qquad 0 \le v \le \infty \tag{1}$$

$$G_w = \begin{cases} 0 & 0 \le v \le v_i, v > v_o \\ (K + K^{'} \times v + K^{''} \times v^2) \times P_r & v_i \le v \le v_r \\ P_r & v_r \le v \le \infty \end{cases} \tag{2}$$

The load in the system is also another source of uncertainty, driven by many spatiotemporal variables, e.g., time, season, weather condition, electricity price, etc. The load uncertainties are modeled in this paper through a Gaussian probability distribution with the PDF in (3).

$$f_{P_D}(P_D) = \frac{1}{\sqrt{2\pi\sigma_{P_D}^2}} exp\left[-\frac{(P_D - \mu_{P_D})^2}{2\sigma_{P_D}^2}\right] \tag{3}$$

2) PTLS Optimization Formulation: Performing a DCOPF-based DTLS optimization for every combination of the generation, load, and network topology is not viable or computationally intensive. The effective application of the Point Estimate Method (PEM) is pursued in this paper to probabilistically model the TLS formulation. Over the other probabilistic techniques [28], PEM is selected due to (i) its high level of accuracy, (ii) its acceptable computational requirements, and (iii) its success record of being implemented in various disciplines. PEM helps effectively capturing the impact of uncertain input variables and the propagation of such uncertainties over the output parameters. The vectors of the input and output random variables are characterized through nonlinear functions presented in (4)-(6), respectively.

$$\mathbf{X} = \left[P_{g,n}^{Wind}, P_{D_n}\right] \tag{4}$$

$$Y = h(\mathbf{X}) = h(x_1, x_2, ...x_n) \tag{5}$$

$$Y = \left[\eta, \pi, GC^t\right] \tag{6}$$

The probabilistic formulation of the DCOPF-based topology control optimization, so called PTLS, is proposed and presented in (7), subject to several system and security constraints in (8)-(13) [14].

$$min\overline{GC^t} = \sum_{g\in\Omega_G, n\in\Omega_B} c_{gn}\overline{P_{gn}^t} \tag{7}$$

$$p_{gn}^{min} \leq \overline{P_{gn}^t} \leq P_{gn}^{max} \quad \forall g \in \Omega_G \tag{8}$$

$$P_k^{min}.\alpha_k \leq P_{knm}^t \leq P_k^{max}.\alpha_k \quad \forall k \in \Omega_L \alpha_k \tag{9}$$

$$\sum_{g\in\Omega_G} \overline{P_{gn}^t} - \sum_{m\in\Omega_B} P_{knm}^t = \sum_{d\in\Omega_D} \overline{P_{dn}^t} \quad \forall n \in \Omega_B \tag{10}$$

$$B_k.(\theta_n - \theta_m) - P_{knm}^t + (1 - \alpha_k).M_k \geq 0 \quad \forall k \in \Omega_L \tag{11}$$

$$B_k.(\theta_n - \theta_m) - P_{knm}^t - (1 - \alpha_k).M_k \leq 0 \quad \forall k \in \Omega_L \tag{12}$$

$$\alpha_k \in \{0, 1\} \quad \forall k \in \Omega_L \tag{13}$$

Constraint (8) limits the output power of generating unit g at node n to its physical capacities. The power flow across transmission line k is limited within the minimum and maximum line capacities in (9). Constraint (10) enforces the power balance at each node. Kirchhoffs laws are incorporated in (11) and (12). An integer variable is introduced in constraint (13) reflecting the status (ON/OFF) of transmission line k in the system. Parameter M_k is a large number, which is used to make the constraints non-binding and relax the one related to the Kirchhoffs laws when a line is removed regardless of the difference in the bus phase angles [14]. M_k is selected by the user in the range of $\mid B_K(\theta^{max} - \theta^{min} \mid$. In order to limit the number of open lines, χ is introduced in (14).

$$\sum_k (1 - \alpha_k) \leq \chi \quad k \in \Omega_L \tag{14}$$

III. The Proposed Methodology

Considering the probability distributions allocated to system uncertain variables, the PEM decomposes (5) into several sub problems by taking into consideration only $2n{+}1$ deterministic values for each uncertain variable located on the right and left side of the mean value. As a result, the PTLS optimization (7)-(13) is simulated $2n + 1$ times for each given set of the uncertain variables, while the other variables are kept constant at their mean values. The $2n+1$ values can be selected either symmetrically or asymmetric around the mean value [28]. Eventually, the PTLS formulation will result in the probability distribution functions (PDF) for the system generation dispatch cost and the most repeated status of each transmission line over the studied probabilistic scenarios.

A. Point Estimation Method (PEM)

Even though PEM is analytically accurate and has been successfully applied to many problems in different disciplines, there are several limitations that can constrain its application to large-scale problems. Three main limitations are as follows [29]: (i) for every selected point in the input vector of random variables, it is a must that the Taylor series of the Z function converge; (ii) infinite terms that exist in the Taylor series and may not match the real dataset in real-world applications; and (iii) only the information regarding the input random variables is required to assess the locations and weighting factors which are independent from the function Z.

1) 2n+1 PEM Scheme: The derivations for the $2n{+}1$ PEM scheme in dealing with a multivariate problem (with multiple random variables) are presented in the following steps [29]:

Step 1: Take the Riemann-Stieltjes integral for the joint distribution function $J(X)$, where X is a vector of $X = (x_1, x_2, x_3, ..., x_n)$. Mathematically, all PEMs will approximate the integral through a weighted sum of several function values assessed at a few selected points of the input random variables X.

$$E(Z^k) = \int_D F^k(X)dJ(X) \tag{15}$$

Step 2: Apply the Taylor series to expand the $Z = F(\mathbf{X})$ at the mean μ_t value of the vector $\mathbf{X}$, where each random variable of X is independent. One can, hence, get:

$$\begin{aligned} Z = \sum_{m_1=0}^{\infty} ... \sum_{m_n=0}^{\infty} \frac{(x_1 - \mu_1)^{m_1}...(x_n - \mu_n)^{m_n}}{m_1! ...m_n!} \\ \cdot \left(\frac{\partial^{(m_1+...+m_n)}F}{\partial x_1^{m_1}...\partial x_n^{m_n}}\right)(\mu_1, ..., \mu_n) \end{aligned} \tag{16}$$

Step 3: μ_z can be written as in (17), if each value of X in (16) converges to $F(X)$:

$$\mu_z = E(F(X)) = \int_D F(x)dJ(x) \tag{17}$$

$$\begin{aligned} = \sum_{m_1=0}^{\infty} ... \sum_{m_n=0}^{\infty} \frac{\lambda_{1,m_1}\sigma_1^{m_1}...\lambda_{n,m_n}\sigma_n^{m_n}}{m_1! ...m_n!} \\ \cdot \left(\frac{\partial^{(m_1+...+m_n)}F}{\partial x_1^{m_1}...\partial x_n^{m_n}}\right)(\mu_1, ..., \mu_n) \end{aligned} \tag{18}$$

Step 4: Let $F(X)$ be $F(\mu_1, ..., \mu_{t-1}, x, \mu_{t+1}, ..., \mu_n)$. The only variable is then X_t, while the other parameters are constant. Applying the Taylor series again, one gets:

$$h_t(x) = h_t(\mu_t) + \sum_{i=1}^{\infty} \frac{1}{i!} h_t^{(i)}(\mu_t)(x - \mu_t)^i \tag{19}$$

Step 5: Set $\xi_{t,1}$ and $\xi_{t,2}$ as the values to be determined, and set $\xi_{t,3}$ to be zero. We then define:

$$S = \sum_{t=1}^{n} (w_{t,1}h_t(x_{t,1}) + w_{t,2}h_t(x_{t,2}) + w_{t,3}h_t(\mu_t)) \tag{20}$$

$$= F(\mu_1, \mu_2, ..., \mu_n) \sum_{t=1}^{n} w_{t,3} + \sum_{i=1}^{\infty} \sum_{t=1}^{n} \frac{1}{i!} h_t^{(i)}(\mu_t)(w_{t,1}\xi_{t,1}^i + w_{t,2}\xi_{t,2}^i)\sigma_t^i \tag{21}$$

Step 6: Both series, S and μ_z, are formed in a similar format. Such a similarity makes it possible to approximate μ_z using S by matching the first few terms. Then, set the following:

$$\sum_{t=1}^{n} (w_{t,1} + w_{t,2} + w_{t,3}) = 1 \tag{22}$$

$$w_{t,1}\xi_{t,1}^i + w_{t,2}\xi_{t,2}^i = \lambda_{t,i} \quad i = 1, 2, 3, 4 \quad t = 1, 2, ..., n \tag{23}$$

and assuming an equal probability for all variables X_t [30],

$$(w_{t,1} + w_{t,2} + w_{t,3}) = \frac{1}{n}, \quad t = 1, 2, ..., n \tag{24}$$

Step 7: Simultaneously solving (23) and (24) for random variable $X_t(t = 1, 2, 3, ..., n)$, the standard location and corresponding wight factors are found as follows:

$$\xi_{t,k} = \begin{cases} \frac{\lambda_{t,3}}{2} + +(-1)^{3-k}\sqrt{\lambda_{t,4} - \frac{3}{4}\lambda_{t,3}^2}, & k = 1, 2 \\ 0, & k = 3 \end{cases} \tag{25}$$

$$w_{t,k} = \begin{cases} (-1)^{3-k} \frac{1}{\xi_{t,k}(\xi_{t,1} - \xi_{t,2})}, & k = 1, 2 \\ \frac{1}{n} - \frac{1}{\lambda_{t,4} - \lambda_{t,3}^2}, & k = 3 \end{cases} \tag{26}$$

Further details on the mathematical formulations above can be found in [29], [30].

2) Two-Point Estimation Method (2-PEM): In this paper, the application of a 2-point PEM (2-PEM) is pursued, where n is selected to be two sample points of the input random variable, one located after and the other before its mean value. Figure 1 illustrates the basic procedure in a 2-PEM algorithm. The following formulations are derived to implement the 2-PEM algorithm for probabilistic TLS optimization as follows [28], [14]: first, the requisite variables for the 2-PEM algorithm are initialized as presented in (27a) and (27b).

$$E(Y)^{(1)} = 0 \tag{27a}$$

$$E(Y^2)^{(1)} = 0 \tag{27b}$$

Then, the location and probability of concentrations are calculated through (28a)-(28d)

$$\xi_{z,1} = \frac{\lambda_{z,3}}{2} + \sqrt{r + (\frac{\lambda_{z,3}}{2})^2} \quad \forall z \in \Omega_Z \tag{28a}$$

$$\xi_{z,2} = \frac{\lambda_{z,3}}{2} - \sqrt{r + (\frac{\lambda_{z,3}}{2})^2} \quad \forall z \in \Omega_Z \tag{28b}$$

$$P_{z,1} = \frac{-\xi_{z,2}}{2r.\sqrt{r + (\frac{\lambda_{z,3}}{2})^2}} \quad \forall z \in \Omega_Z \tag{28c}$$

$$P_{z,2} = \frac{-\xi_{z,1}}{2r.\sqrt{r + (\frac{\lambda_{z,3}}{2})^2}} \quad \forall z \in \Omega_Z \tag{28d}$$

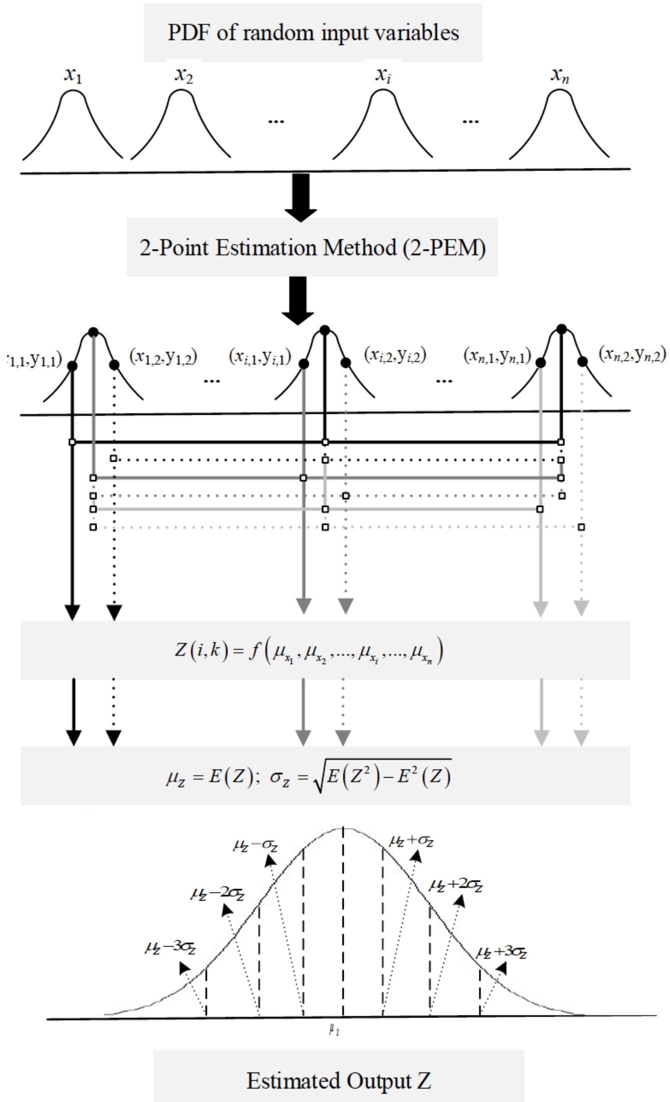

Fig. 1. Basic procedure of the PEM algorithm [31].

One can then calculate the two concentrations $x_{z,1}$ and $x_{z,2}$ using the following equations:

$$x_{z,1} = \mu x, z + \xi_{z,1}.\sigma x, z \tag{29a}$$

$$x_{z,2} = \mu x, z + \xi_{z,2}.\sigma x, z \tag{29b}$$

The next step is to run the deterministic TLS optimization with respect to the vector $\mathbf{X}$ for concentrations $x_{z,1}$ and $x_{z,2}$:

$$\mathbf{X} = [\mu_{z,1}, \mu_{z,2}, ..., x_{z,i}, ..., \mu_{z,r}] \quad i = 1, 2 \tag{30}$$

The following equations are then updated:

$$E(Y)^{(z+1)} \cong E(Y)^{(z)} + \sum_{i=1}^{2} P_{z,i}.h(\mathbf{X}) \tag{31a}$$

$$E(Y^2)^{(z+1)} \cong E(Y^2)^{(z)} + \sum_{i=1}^{2} P_{z,i}.h^2(\mathbf{X}) \tag{31b}$$

TABLE I
12-HOUR TIME-SERIES DATA OF UNCERTAIN WIND PATTERNS AND LOAD PROFILES

Time	P_w	P_d(1)	P_d(2)	Time	P_w	P_d(1)	P_d(2)
1	40	277	317	7	55	307	288
2	80	250	319	8	65	309	260
3	70	230	330	9	100	318	250
4	30	350	270	10	90	285	330
5	35	300	290	11	70	270	320
6	90	200	255	12	45	266	210

And finally, the expected value and the associated standard deviation of the output variables are found in (32):

$$\mu_Y = E(Y) \tag{32a}$$

$$\sigma_Y = \sqrt{E(Y^2) - E^2(Y)} \tag{32b}$$

B. Correlation of Uncertainties and Scenario Reduction

If focusing on the conventional procedure in a $2n$+1 PEM (or 2-PEM), $2n+1$ (or 2) number of scenarios are generated for each random variable and the DTLS optimization problem should run for $2n$+1 (or 2) times concerning the random variable of interest. As the number of random input variables increases, the number of required DTLS simulation scenarios exponentially increases. All generated scenarios are assigned an equal realization probability of $1/\tau$. Considering the implementation requirements of the PTLS optimization in large-scale power grids with many random variables and in an operational time-frame (hourly), a dimensionality reduction technique is needed to handle the sheer number of possible scenarios, making it computationally attractive.

A simple, yet efficient, scenario reduction technique is employed in this paper. A two-dimensional matrix D, where $D \in R_+^{(N_R+1)\times\tau}$, is generated first, representing the random input variables, i.e., the intermittent generation and stochastic load profiles. The length of the data is considered equal to τ, and each row in matrix D represents a particular dataset for the generation or load. The maximum and minimum values will be evaluated in each row of the matrix D, and all the other values between the maximum and minimum values are distributed into B_i number of bins, where $i \in [1, 2, 3, ..., (N_R+1)]$. The number of bins B is here arbitrarily selected and the axis of each bin is (N_R+1). Each bin is here representing one scenario, where the probability of each scenario is the number of counts inside the bin divided by the total number of the data points. The number of cells in each array is assigned a boundary of τ, reflecting the fact that at most τ number of cells is allocated values greater than zero [32].

An illustrative example is provided here to demonstrate the procedure of the scenario reduction technique. Table III presents 12-hour time series corresponding to a 120 MW wind generator P_w and two loads ($P_d(1)$ and $P_d(2)$). The maximum and minimum values for the wind generation and the loads are [30-100] MW, [200-350] MW, and [211-330] MW, respectively. Each time series is normalized with respect to its corresponding maximum value. Three dimensional bins (3×3) should be set up optionally, representing the 3 number of random inputs variables (load 1, load 2, and the wind generation), respectively. Each normalized value is distributed into the associated bin, and the number of observed values that fall in each bin is counted. Note that since the three-dimension bins are in form of a $3\times3\times3$ array, the maximum number of possible scenarios is 27 [32].

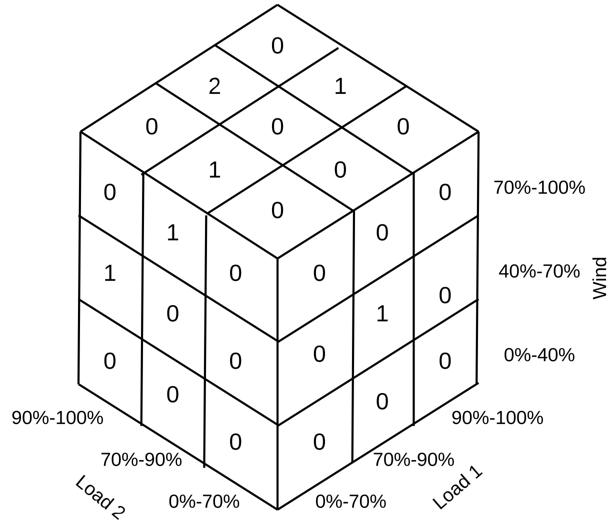

Fig. 2. The generated three-dimensional bins for scenario reduction.

Figure 2 illustrates the counted number of data points in each bin. The middle cell in load 1 direction shows that the load 1 varies between 70% to 90% and load 2 changes between 0% to 70% of their maximum values, while the wind generation is 40% to 70% of its capacity. Note that this observation occurs in one particular hour (in 12 hours). The probability of each scenario is the value of each cell divided by the number of total hours (e.g., 1 by 12 for this cell).

IV. NUMERICAL CASE STUDIES: MODIFIED IEEE 118-BUS TEST SYSTEM

A. System Descriptions, Data, and Assumptions

The proposed approach is implemented on the IEEE 118-bus test system which consists of 185 transmission lines and 19 generating units (see Fig. 3) with 6859.2 MW installed capacity and a peak demand of 6000 MW. All system data (i.e., the hourly generation and load profiles, historical wind data, transmission line parameters, etc.) are provided in [33].

B. Results and Discussions

In order to demonstrate the performance of the suggested PTLS optimization and the solution technique, four different test cases (TC) are studied: TC#1 is the base-case study in which a deterministic OPF is performed with no topology control action allowed. TC2 and TC3 represent the cases in which DTLS (with known and accurate forecasts available, thereby solving a deterministic optimization) and PTLS (uncertainties are modeled) are performed, respectively. In TC3, 101 input random variables (2 wind generating units and 99 loads) are considered, resulting in 202 scenarios probabilistically handled via the 2-PEM. In TC4, the scenario reduction technique is applied to the PTLS optimization. The optimization problem

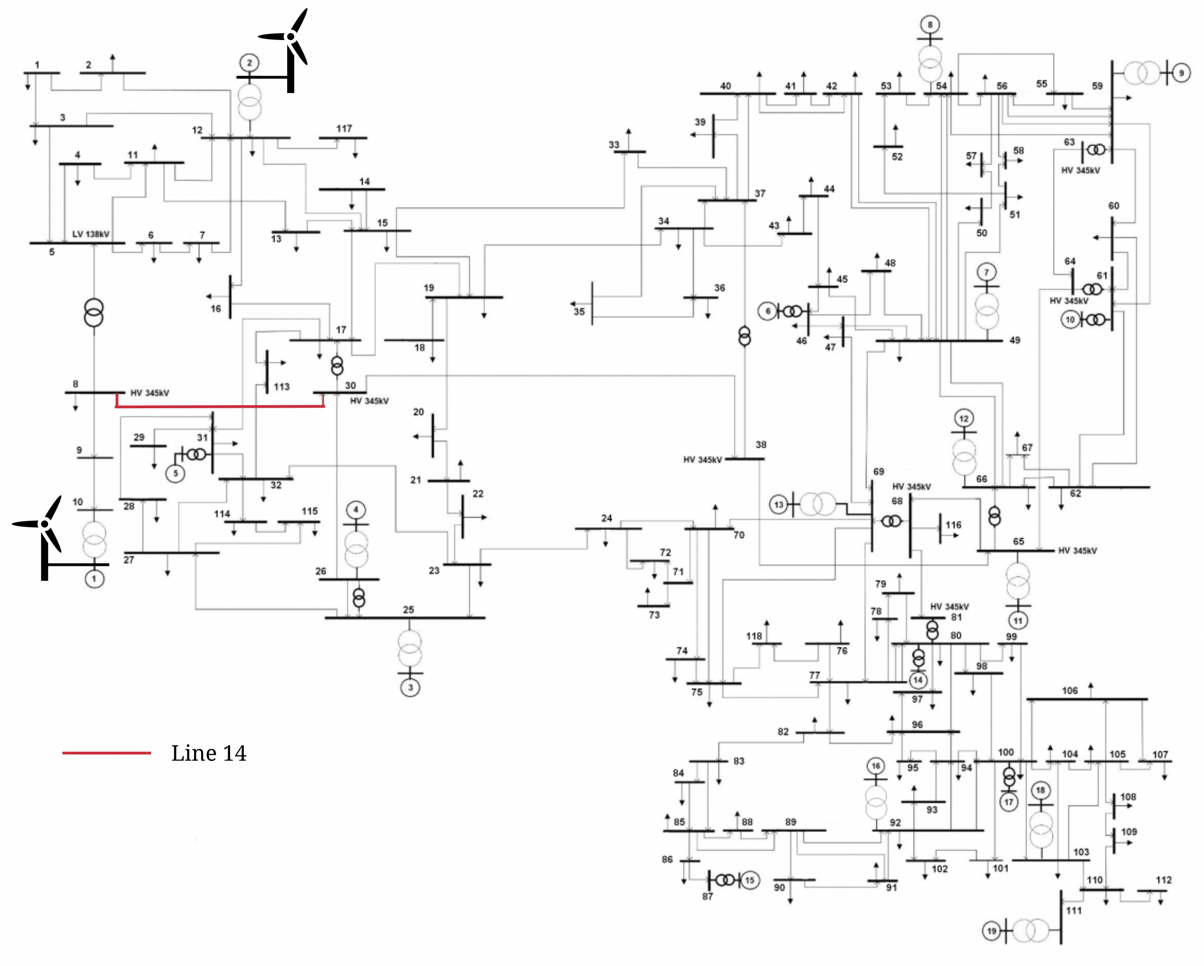

Fig. 3. The IEEE 118-bus test system configuration.

in all cases is run in General Algebraic Modeling System (GAMS) environment, using a Dell PowerEdge R815 with 4 AMD Opteron 6174 Processors (48 2.2 GHz cores) and 256 GB of Memory running CentOS 5.7.

Simulation results, in terms of the system operation cost, the switching solutions, and the computational times in different test cases are presented in Table II. Comparing the results in TC2 and TC3 with the base-case TC1, one can easily observe the economic advantages of harnessing the network built-in flexibility and topology control. TC2 will result in a total system cost of 632.682$, with transmission line 14 switched open. The computation time for TC2 is reported 4.16 seconds. The objective function and the computation time in TC3 are found 629.596978 and $2341.64sec$, respectively. In TC4, where the correlations of the system uncertainties are managed through a scenario reduction technique, a reduced number of 5 scenarios is resulted. The PTLS optimization runs only 5 times, as opposed to TC3 with 202 simulations. Table III shows the concentrations found in each scenario. The total system operation cost in TC4 is found $635.4567$$ and Table IV summarizes the cost and simulation run-time in each scenario. Eventually, the dispatch solutions of the generating units in each studied test case are demonstrated in Fig. 4.

TABLE II
SIMULATION RESULTS IN DIFFERENT STUDIED TEST CASES

Case #	Operation Cost ($)	Time (sec.)	Switching Line
TC1	639.86894	0.1	Not Allowed
TC2	632.682627	4.16	14
TC3	629.596978	2341.64	14
TC4	635.4567	12.83	14

TABLE III
CONCENTRATION FOR EACH BIN

Generation \ Load	90%- 93%	93%- 96%	96%- 100%
90%- 93%	0	2	0
93%- 96%	99	202	99
96%- 100%	0	2	0

V. CONCLUSION

This paper presented a probabilistic DCOPF-based formulation for the hour-ahead optimal topology control in power systems considering the correlations of stochastic variables. This probabilistic approach conjoins the Point-Estimate Method (PEM) and a scenario reduction technique to statistically model and incorporate the system uncertainties (wind generation and load). Simulation Results on the modified IEEE

TABLE IV
OPERATION COST AND TIME FOR EACH CASE SCENARIO

Scenario #	Operation Cost ($)	Time (sec.)
S1	637.025525	3.52
S2	601.786825	3.64
S3	633.301306	1.64
S4	673.636879	1.7
S5	628.335681	2.33

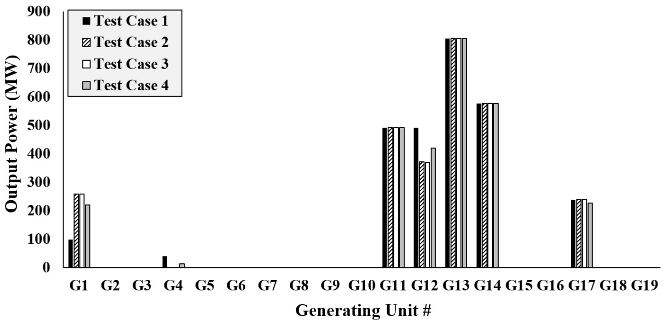

Fig. 4. Generation dispatch in different studied test cases.

118-bus test system demonstrated that the proposed probabilistic topology control framework with a scenario reduction technique can simultaneously and significantly improve the operation cost-effectiveness and computational efficiency of the power grid operation optimization.

REFERENCES

[1] M. Rezaeian Koochi, S. Esmaeili, and P. Dehghanian, "Coherency detection and network partitioning supported by wide area measurement system," in *2018 IEEE Texas Power and Energy Conference (TPEC)*. IEEE, 2018, pp. 1–6.

[2] M. Rezaeian Koochi, P. Dehghanian, S. Esmaeili, P. Dehghanian, and S. Wang, "A synchrophasor-based decision tree approach for identification of most coherent generating units," in *44th Annual Conference of the IEEE Industrial Electronics Society (IECON)*. IEEE, 2018, pp. 71–76.

[3] H. Glavitsch, "Switching as means of control in the power system," *International Journal of Electrical Power & Energy Systems*, vol. 7, no. 2, pp. 92–100, 1985.

[4] W. Shao and V. Vittal, "Corrective switching algorithm for relieving overloads and voltage violations," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1877–1885, 2005.

[5] A. A. Mazi, B. F. Wollenberg, and M. H. Hesse, "Corrective control of power system flows by line and bus-bar switching," *IEEE Transactions on Power Systems*, vol. 1, no. 3, pp. 258–264, 1986.

[6] A. Khodaei and M. Shahidehpour, "Transmission switching in security-constrained unit commitment," *IEEE Transactions on Power Systems*, vol. 25, no. 4, pp. 1937–1945, 2010.

[7] F. Kunz, "Congestion management in germany-the impact of renewable generation on congestion management costs," in *Seventh Conf. Econ. Energy Mark*, 2011.

[8] P. Dehghanian, Y. Wang, G. Gurrala, E. Moreno-Centeno, and M. Kezunovic, "Flexible implementation of power system corrective topology control," *Electric Power Systems Research*, vol. 128, pp. 79–89, 2015.

[9] P. Dehghanian, S. Aslan, and P. Dehghanian, "Maintaining electric system safety through an enhanced network resilience," *IEEE Transactions on Industry Applications*, vol. 54, no. 5, pp. 4927–4937, Sept.-Oct. 2018.

[10] E. B. Fisher, R. P. O'Neill, and M. C. Ferris, "Optimal transmission switching," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1346–1355, 2008.

[11] M. Kezunovic, T. Popovic, G. Gurrala, P. Dehghanian, A. Esmaeilian, and M. Tasdighi, "Reliable implementation of robust adaptive topology control," in *System Sciences (HICSS), 2014 47th Hawaii International Conference on*. IEEE, 2014, pp. 2493–2502.

[12] P. Dehghanian, T. Popovic, and M. Kezunovic, "Circuit breaker operational health assessment via condition monitoring data," in *North American Power Symposium (NAPS), 2014*. IEEE, 2014, pp. 1–6.

[13] P. Dehghanian and M. Kezunovic, "Impact assessment of transmission line switching on system reliability performance," in *Intelligent System Application to Power Systems (ISAP), 2015 18th International Conference on*. IEEE, 2015, pp. 1–6.

[14] ——, "Probabilistic decision making for the bulk power system optimal topology control," *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 2071–2081, 2016.

[15] M. Soroush and J. D. Fuller, "Accuracies of optimal transmission switching heuristics based on dcopf and acopf," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 924–932, 2014.

[16] K. W. Hedman, M. C. Ferris, R. P. O'Neill, E. B. Fisher, and S. S. Oren, "Co-optimization of generation unit commitment and transmission switching with n-1 reliability," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1052–1063, 2010.

[17] R. P. O'Neill, R. Baldick, U. Helman, M. H. Rothkopf, and W. Stewart, "Dispatchable transmission in rto markets," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 171–179, 2005.

[18] P. A. Ruiz, J. M. Foster, A. Rudkevich, and M. C. Caramanis, "On fast transmission topology control heuristics," in *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011, pp. 1–8.

[19] J. D. Fuller, R. Ramasra, and A. Cha, "Fast heuristics for transmission-line switching," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1377–1386, 2012.

[20] P. A. Lipka, R. P. O'Neill, S. S. Oren, A. Castillo, M. Pirnia, and C. Campaigne, "Optimal transmission switching using the iv-acopf linearization," Univ. of California, Berkeley, CA (United States), Tech. Rep., 2013.

[21] F. Qiu and J. Wang, "Chance-constrained transmission switching with guaranteed wind power utilization," *IEEE Trans. Power Syst*, vol. 30, no. 3, pp. 1270–1278, 2015.

[22] A. S. Korad and K. W. Hedman, "Robust corrective topology control for system reliability," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4042–4051, 2013.

[23] M. H. Taheri, S. Dehghan, M. Heidarifar, and H. Ghasemi, "Adaptive robust optimal transmission switching considering the uncertainty of net nodal electricity demands," *IEEE Systems Journal*, 2015.

[24] J. Seguro and T. Lambert, "Modern estimation of the parameters of the weibull wind speed distribution for wind energy analysis," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 85, no. 1, pp. 75–84, 2000.

[25] R. Billinton, H. Chen, and R. Ghajar, "A sequential simulation technique for adequacy evaluation of generating systems including wind energy," *IEEE Transactions on Energy Conversion*, vol. 11, no. 4, pp. 728–734, 1996.

[26] A. N. Celik, "A statistical analysis of wind power density based on the weibull and rayleigh models at the southern region of turkey," *Renewable energy*, vol. 29, no. 4, pp. 593–604, 2004.

[27] E. C. Morgan, M. Lackner, R. M. Vogel, and L. G. Baise, "Probability distributions for offshore wind speeds," *Energy Conversion and Management*, vol. 52, no. 1, pp. 15–26, 2011.

[28] E. Rosenblueth, "Point estimates for probability moments," *Proceedings of the National Academy of Sciences*, vol. 72, no. 10, pp. 3812–3814, 1975.

[29] Z. Lin and W. Li, "Restrictions of point estimate methods and remedy," *Reliability Engineering & System Safety*, vol. 111, pp. 106–111, 2013.

[30] H. Hong, "An efficient point estimate method for probabilistic analysis," *Reliability Engineering & System Safety*, vol. 59, no. 3, pp. 261–267, 1998.

[31] P. Dehghanian, "Power system topology control for enhanced resilience of smart electricity grids," Ph.D. dissertation, 2017.

[32] O. Ziaee, O. Alizadeh-Mousavi, and F. F. Choobineh, "Co-optimization of transmission expansion planning and tcsc placement considering the correlation between wind and demand scenarios," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 206–215, 2018.

[33] "Data information," https://www.flipsnack.com/mohannadalhazmi/data.html, accessed: 2010-09-30.